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DEVELOPMENT OF A HYBRID FUZZY DECISION SUPPORT SYSTEM FOR ASSESSING THE EFFECTIVENESS OF ARTILLERY FIRE IN CONDITIONS OF UNCERTAIN DISTURBANCES

The object of research is the processes of determining the effectiveness of artillery fire under conditions of uncertain disturbances, which include wear of the gun barrel, deterioration of the quality of charges and shells of a certain batch. This work addresses the problem of ensuring the adequacy of assessing the effectiveness of artillery fire in cases where the parameters of the gun barrel, the quality of powder charges or shells deviate from the nominal values and are determined inaccurately.

The research used fuzzy logic methods to formalize decision-making processes under conditions of uncertainty, as well as methods of mathematical modeling and statistical analysis to simulate firing sequences and determine effectiveness estimates.

A hybrid fuzzy-logical decision support system (DSS) has been developed and tested, which allows for a comprehensive and highly accurate assessment of the effectiveness of artillery fire. When forming estimates, the DSS takes into account three key parameters that characterize the most significant sources of uncertainty: barrel wear, deterioration of the quality of charges, deterioration of the quality of shells.

The results of computational experiments for various realistic artillery fire scenarios were obtained. In turn, artillery installations with initial barrel wear values of 0.1 and 0.25 were studied when using charges and shells of different quality. During the experiments, it was established that the proposed system provides an adequate, practically useful assessment of the fire efficiency of artillery installations under realistic conditions of uncertainty. In particular, the calculated efficiency values during the entire firing process changed by no more than 12% in the first three experiments and no more than 21% in the next three.

The developed DSS can be used in modern artillery complexes to increase the efficiency of making control decisions, reduce the proportion of misses, save scarce ammunition and reduce the risk of damage to equipment and personnel.

Keywords: *artillery fire, efficiency assessment, barrel wear, decision support system, fuzzy logic.*

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1. Introduction

Despite the increasing use of unmanned aerial vehicles (UAVs), autonomous robotic systems, and precision-guided munitions in modern warfare, artillery still plays an important role in warfare [1]. Modern UAVs can provide real-time target acquisition and guidance, as well as higher accuracy. However, they do not have such a destructive effect, and do not provide both high speed and wide coverage area as conventional artillery fire [2]. Compared with modern high-precision firepower of various types that have real-time correction functions, traditional field artillery has advantages in terms of ease of use, insensitivity to electronic warfare, and cost [3]. The fighting in the Russian-Ukrainian war also showed that field artillery is one of the main means of inflicting fire damage on the enemy and successfully achieving operational-tactical level objectives [4]. Despite the fact that firepower and tactical techniques for their use are constantly being improved, the effectiveness of combat operations of various types still significantly depends on the accuracy, coordination of actions and the overall effectiveness of artillery fire [5]. However, the analysis of combat operations in modern conditions of high intensity shows the urgent need to transition from traditional methods of massed fire to fundamentally new approaches to the use of artillery [6]. The main requirements that are currently imposed on artillery systems are: high rate of fire and accuracy of fire, minimizing the consumption of ammunition to destroy one target and minimizing the time spent in positions when performing a fire mission [7]. Also, additional difficulties arise due to a number of limitations and the presence of constantly acting disruptive influences, including accelerated wear of gun barrels due to their high-intensity use, the growing shortage of ammunition, as well as their low quality and other uncertainties [8]. All these factors significantly worsen the combat capabilities of artillery systems when using traditional decision-making models, control methods and diagnostics. Thus, today there is an urgent need to develop new computational methods and models for automatic control, decision-making and diagnostics systems in artillery installations and complexes.

To date, scientists from different countries of the world have already developed quite a lot of different models, methods, information technologies and software and hardware to improve the critically important characteristics of artillery systems [9]. In particular, in the work [10] a comprehensive study of the features of the use of simulation modeling systems in the design of artillery systems with specified characteristics was conducted. In turn, to increase the accuracy of firing, advanced mathematical models that take into account the five degrees of freedom of the projectile [11] and basic meteorological data [12] during the flight can be quite effectively used. Also, to take into account rounding errors when entering the main parameters, it is advisable to use the model given in [13]. A significant increase in the effectiveness of counter-battery combat can be achieved using a model for determining the coordinates of the firing positions of guns that move during firing [14].

To increase survivability and the percentage of target hits, a method for determining positions for moving guns based on Markov chains was proposed in [15]. In turn, highly effective methods for controlling artillery assets to suppress landing operations were developed in [16], which are also based on Markov models to take into account the probabilistic aspects of target hits. In addition, heuristic optimization methods can be used quite effectively, both to increase the accuracy of gun stabilization systems [17] and the overall efficiency [18] of various types of artillery systems.

In addition, specialized intelligent information systems have been developed that contain algorithms for improving the processes of creating firing tables [19], coordinated control of units [20], and effective distribution of fire tasks [21]. The use of these systems makes it possible to significantly increase the effectiveness of interaction between artillery units during the joint performance of combat missions of various types. However, the main drawback of these developments and the vast majority of other existing models and methods is that they allow achieving the desired results when using artillery installations and complexes in nominal or clearly defined operating conditions. In particular, they assume the use of fully serviceable and unworn guns, homogeneous batches of ammunition with precisely specified characteristics, and do not take into account a number of other uncertainties that characterize modern high-intensity combat conditions. At the same time, an analysis of the current realities of large-scale combat operations has shown that artillery installations and systems operate under a number of uncertain disturbances [22]. These disturbances in many cases significantly reduce the effectiveness of the tasks and can lead to the complete failure of artillery equipment [23]. Such disturbances include, first of all, progressive barrel wear, which occurs due to an excessively large number of shots per gun [24]. A worn gun barrel is one of the main factors that significantly worsens the ballistic characteristics of the shot and reduces its accuracy [25]. In turn, the level of wear of the barrel of an artillery gun can be determined based on the initial velocity of the projectile and the acoustic fields of the shot, as given in [26].

Additional disturbing influences are also aging or degradation of the characteristics of the powder charge and changes in the mass or geometry of the projectile (due to manufacturing tolerances, defects, non-compliance with storage/processing rules, combat damage and other external factors).

To solve the problem of taking into account individual uncertainties, a concept of artillery fire verification has recently been proposed, which allows detecting undesirable deviations from the specified values of the parameters of individual shots. In particular, in work [27] a verification method was developed that allows fairly accurately determining the coordinates of the projectile's collision with the surface before its fall and detonation. This significantly improves accuracy, and also reduces the firing time and the total time of units at firing positions. When using the above method, it becomes possible to make operational adjustments even during the projectile's flight. In turn, in the event of significant deviations from the current values of the initial velocity of the projectile's departure and its speed in certain sections of the trajectory, a decision can be made to cease fire and leave the position. This will reduce the risk for the artillery installation and its calculation in the event of the impossibility of completing the task. Also, in work [28] an approach to projectile quality control based on optimized sampling algorithms is proposed. The use of the above algorithms allows for specialized sorting of ammunition and determination of deviations in projectile parameters, which ensures an overall increase in the efficiency of using artillery installations in conditions of resource shortage.

However, despite some progress in this direction, the problem of determining a mathematically formalized assessment of the effectiveness of firing with a comprehensive account of the influence of the main uncertain disturbances still remains unresolved. In addition, there is a need to determine the effectiveness not only for a single shot, but also during the long-term use of artillery installations for entire batches of charges and shells.

Currently, the assessment of the overall effectiveness of firing for making decisions on the advisability of continuing firing and the general possibility of conducting combat operations is carried out manually by commanders based on their personal experience and analysis of the received heterogeneous information. In conditions of intensive, rapidly changing combat operations, the negative impact of the human factor significantly increases, which can lead to making a number of erroneous decisions with subsequent failure to complete the task and possible losses of personnel and equipment. Analysis of the accumulated statistics of the results of previous firings also does not allow obtaining adequate assessments, since the wear of guns accumulates intensively, and the quality of charges and shells in new batches may differ significantly from the previous ones.

Thus, to adequately assess the overall effectiveness of artillery fire in automatic mode, with comprehensive consideration of various types of uncertain disturbances, it is advisable to have a specialized decision support system. To use expert data and knowledge of experienced commanders in decision-making processes, the presented decision support system (DSS) should be based on intellectual principles that effectively apply models of human reasoning and accumulated experience. Therefore, for the construction of an intellectual DSS of this type, the most appropriate is to use the mathematical apparatus of fuzzy sets and fuzzy logic [29]. In turn, fuzzy logic allows to formalize linguistic statements and human decision-making mechanisms [30]. Fuzzy-logical models of various types effectively combine quantitative and qualitative assessments using linguistic terms (LT) and membership functions (MF) [31]. In addition, fuzzy systems allow processing noisy and incomplete data, as well as creating sets of interpretable, easily verifiable logical chains of premises and conclusions in the form of a rule base [32]. To increase the adequacy of the resulting decisions, it is advisable to hybridize the given fuzzy DSS with a model that will analyze the already accumulated real data collected when using the current batch of ammunition on a given artillery installation.

The object of research is the processes of determining the effectiveness of artillery fire under conditions of uncertain disturbing influences, which include wear of the gun barrel, reduction in the quality of charges and the quality of shells of a certain batch.

The aim of research is to develop and test a hybrid fuzzy decision support system for a comprehensive assessment of the effectiveness of artillery fire under conditions of uncertain disturbances. The resulting system can be used both directly in combat conditions and in simulators for training personnel of artillery units.

To achieve the aim, it is necessary to solve the following objectives:

1. Development of a functional architecture of a hybrid fuzzy DSS for a comprehensive assessment of the effectiveness of artillery fire.
2. Synthesis of the fuzzy subsystem of the proposed hybrid DSS.
3. Conducting a series of computational experiments to study the effectiveness of the developed hybrid DSS.

2. Materials and Methods

This research used fuzzy logic methods to formalize decision-making processes when assessing the effectiveness of artillery fire under variable and uncertain conditions. Mathematical modeling and statistical analysis methods were also used to simulate firing sequences and determine effectiveness estimates.

This paper considers three main classes of uncertain disturbances that significantly reduce the effectiveness of artillery fire in short-term and long-term use: progressive wear of the gun barrel, deterioration of the properties of powder charges, and deviation of projectile characteristics from nominal ones.

Artillery barrel wear is a progressive mechanical destruction of the barrel bore and charging chamber, which significantly changes the initial conditions of projectile launch and, accordingly, worsens their ballistic characteristics during further flight. In turn, barrel wear gradually occurs during firing due to thermal erosion from hot powder gases, the negative impact of the chemical action of combustion products, as well as the abrasive interaction of the projectile leading belts with the rifling of the barrel bore. In this work, let's denote the normalized barrel wear index as W_b, $W_b \in [0,1]$. In this case, the value $W_b = 0$ corresponds to a completely new barrel manufactured with nominal parameters and fully suitable for operation, and the value $W_b = 1$ – to a barrel worn out to such an extent that accurate firing from it becomes impossible. The main sign of gun barrel wear with unchanged nominal values of all other parameters of the artillery installation is a decrease in the initial velocity of the projectile υ_0. Thus, when the initial velocity υ_0 decreases by 10% or more from the nominal value υ_{0n}, the gun barrel is considered completely worn out ($W_b = 1$) [26]. In turn, the dependence of the initial projectile departure velocity υ_0 on the barrel wear W_b can be generally represented as follows

$$\upsilon_0 = \upsilon_{0n} f\left(1 - W_b\right), \tag{1}$$

where f can be given by various linear or nonlinear functions.

Mainly, the wear of the barrel depends on the total number of shots fired from it and the characteristics of each shot (maximum pressure in the barrel, combustion temperature and other properties of the powder charge, geometry of the projectile). In addition, the wear of the gun barrel is additionally affected by the intensity of shooting, the features of technical maintenance and cleaning, as well as certain environmental factors (humidity, pollution, etc.). In turn, the dependence of the wear of the barrel of an artillery system on the number of shots fired can be represented by various functions. For example, when using a function with several linear sections having different slopes, the expression can be used

$$W_b = \begin{cases} k_{w1} N_{sh} + b_{w1}, \text{ at } 0 < N_{sh} \le N_{sh1}; \\ k_{w2} N_{sh} + b_{w2}, \text{ at } N_{sh1} < N_{sh} \le N_{sh2}; \\ k_{w3} N_{sh} + b_{w3}, \text{ at } N_{sh2} < N_{sh} < N_{shmax}; \\ 1, \text{ at } N_{sh} \ge N_{shmax}, \end{cases} \tag{2}$$

where N_{sh} – the number of shots fired; N_{sh1} and N_{sh2} – certain given values of the number of shots at which the slope of the characteristic changes; N_{shmax} – the maximum number of shots for which the barrel of this gun is designed. In turn, k_{w1}, k_{w2}, k_{w3} – the coefficients that determine the corresponding slopes of the characteristic; b_{w1}, b_{w2}, b_{w3} – the values of the shift of the corresponding characteristics. In this case, for new barrels $b_{w1} = 0$.

A sigmoid function can also be used

$$W_b = \frac{1}{1 + e^{-\alpha\left(N_{sh} - \beta\right)}}, \tag{3}$$

where α and β are adjustable coefficients.

Barrel wear can be accurately measured in laboratory conditions using bore inspection tools, including high-resolution borescopes, laser profilometers, and various types of coordinate measurement systems. These tools allow for the determination of various types of mechanical damage to the bore. Also, metallurgical analysis methods can be used to determine the degree of corrosion and thermal damage. In field conditions, barrel wear is determined indirectly, namely by deviations in the ballistic, acoustic, and visual characteristics of shots.

In artillery charges used to fire shots, the output energy and properties of thermal processes significantly depend on the composition of the gunpowder, as well as the geometry and microstructure of its granules. These features, as well as manufacturing tolerances, significantly affect the resulting muzzle energy and other parameters of the shot. Deterioration of the characteristics of the charges can be caused by improper storage and transportation conditions, various types of physical damage and too long storage periods due to aging and degradation of the gunpowder. These factors lead to a change in the burning rate, a decrease in muzzle energy and, accordingly, to significant deviations of the initial velocities of the shells from the nominal values. Also, an additional negative consequence of the use of low-quality charges is increased wear of the gun barrels. Thus, the difference in the quality of the powder charges in different batches of ammunition creates additional uncertain disturbances that significantly affect the firing processes from artillery installations. In this work, the relative quality of the powder charges is denoted as $Q_c \in [0,1]$, where the value $Q_c = 0$ corresponds to the lowest quality, at which accurate shooting with all other nominal parameters is no longer possible. In turn, the value $Q_c = 1$ corresponds to the highest quality, at which all charge parameters have nominal values. The low quality of the powder charge Q_c also significantly reduces the initial velocity of the projectile υ_0 and accelerates the wear of the barrel W_b of the artillery installation.

Various laboratory methods and tools can be used to accurately determine the characteristics of powder charges. The total energy output, the speed characteristics of thermal processes and the value of the maximum pressure achieved are usually determined by burning test samples of powder in closed tanks. The combustion temperature and mass change parameters are determined using differential scanning calorimetry and thermogravimetric analysis. At the same time, defects in the structure of granules and chemical degradation can be determined in the process of microscopic and spectroscopic studies. In field conditions, conducting such analyses is problematic, therefore, test firing of charges from certain batches is most often used, the quality of which is determined indirectly by the characteristics of the shots fired.

Artillery shells are also prone to mechanical damage and may have deviations in the main characteristics due to the presence of production defects. The main possible deviations of the shell are deviations in mass, center of gravity, symmetry and surface roughness. For example, an increase in mass or a shift in the center of gravity can significantly reduce the initial speed and stability of the subsequent flight, which will definitely lead to a deviation from the desired trajectory and, accordingly, from the point of impact on the surface. Thus, a decrease in the quality of shells significantly affects the reduction of the accuracy of fire and an increase in the total amount of ammunition spent on hitting and destroying the target.

To denote the relative quality of shells in this work, the variable Q_p is used. In this case, $Q_p = 0$ corresponds to the lowest quality value at which accurate shooting is impossible. The value $Q_p = 1$ corresponds to the highest quality at which all shell parameters have nominal values. In turn, in addition to reducing the accuracy of shooting, the reduced quality of shells also increases the wear of the gun barrel to a certain extent.

In laboratory conditions, various types of coordinate measurement devices, laser profilometry and high-precision scales are used for a comprehensive determination of the quality of shells. Also, to determine internal defects (internal voids or delaminations) can be used radiography and metallography devices. In turn, directly at the positions, the quality of shells is determined by their visual and tactile inspection, and portable scales can also be used for additional weight control.

The effectiveness of artillery fire η is defined as the ratio of the number of successful shots N_{shs} to the total number of shots N_{sh}, fired from one installation with a certain value of the initial barrel wear W_b when using a given batch of charges and shells

$$\eta = \frac{N_{shs}}{N_{sh}}. \tag{4}$$

In turn, a shot is considered successful if it hits within the permissible dispersion circle around a specified target, which is usually taken as 1% of the firing range. For example, for a target located at a distance of 10,000 m from the gun, the permissible dispersion radius is 100 m. The total number of shots N_{sh} is determined by the number of all shots already fired at the current moment from a given gun during the execution of a fire mission using the current batch of shells and charges with specified quality indicators. For example, this may be 100 or even 1,000 shots fired from one batch of shells and charges over several days or weeks. The assessment of the effectiveness of the shooting is carried out for each individual installation, since in modern combat conditions, artillery installations are usually dispersed at large distances from each other. Thus, they can use different batches of transported shells and charges during the execution of a common fire mission.

It is very important to make a preliminary assessment of the firing efficiency η (based on the barrel wear values W_b, projectile quality Q_p and charge quality Q_c) and then compare it with a given threshold value η_s (e. g. $\eta_s = 0.5$). This allows for informed decisions to be made on whether to continue or stop artillery firing. If the determined value η is lower than the set threshold value η_s, various measures can be taken to reduce the risks. The main ones are replacing this artillery installation with another one with a lower barrel wear value and temporarily stopping firing until another batch of higher quality ammunition arrives. Also, the current batch can be redistributed to perform other fire tasks (e. g. area firing) or the installation with personnel can be withdrawn to avoid losses. Since the efficiency value η is calculated directly at the firing positions based on the current values of the input data, the commanders of artillery units receive up-to-date and reliable information for decision-making even before the start of firing. This allows to save scarce ammunition, reduce the overall risks of combat operations and prevent additional unnecessary wear of guns in cases where the predicted fire efficiency is too low. In addition, the efficiency indicator η can be used as the probability of successful completion of a certain fire task when calculating the mathematical expectation based on known evaluation functions for further making mathematically sound decisions. To determine a preliminary assessment of the efficiency of artillery fire η based on the current values of the above-mentioned uncertain disturbances (W_b, Q_c, Q_p), in this work it is advisable to develop a decision-making support system based on fuzzy logic. Fuzzy DSS have shown quite high efficiency in solving diverse tasks of decision-making, diagnostics and control in various industries, including industrial automation and energy [33], transport [34], defense systems and complexes [35]. The main advantage of these systems is the ability to formalize expert knowledge and reasoning, as well as to ensure adequate functioning in conditions of incomplete or inaccurate data [36]. By integrating heterogeneous quantitative information and heuristic knowledge in logically transparent linguistic rules, fuzzy DSS provide flexible and interpretable decision-making in situations where traditional analytical models are ineffective [37]. Given the multifactorial and uncertain nature of the artillery fire process, the effectiveness of which is affected by variable wear of the gun barrel, degradation of powder charges and deviations in projectile characteristics, the use of fuzzy DSS is both technically and operationally justified. This system will allow assessing the effectiveness of firing in real time under conditions of uncertain disruptive influences and will facilitate making optimal command decisions regarding the appropriateness of continuing, adjusting, or terminating fire missions.

Fuzzy DSS of the Mamdani type are currently one of the most widely used systems that have proven themselves well in modeling the processes of human logical thinking under conditions of uncertainty [38]. They provide high interpretability, formation of intuitively understandable conclusions based on rules, and adequate functioning in solving a wide range of management and decision-making tasks [39]. Given the need to provide transparent, expert assessments of the effectiveness of artillery fire, the proposed DSS is expedient to implement it on the basis of Mamdani fuzzy logical inference. Next, let's consider the main stages of designing a fuzzy DSS of the Mamdani type for assessing the effectiveness of artillery fire. The structural diagram of this DSS is shown in Fig. 1. Next, let's consider the main elements and signals of this scheme. The KB block is a knowledge base, which stores all data regarding linguistic terms and their membership functions with set parameters. The RB block is a rule base that contains all the rules created by experts. In turn, FZ, AGG, ACT, ACC and DFZ are fuzzification, aggregation, activation, accumulation and defuzzification blocks that implement these operations in the process of fuzzy inference. The **Z** vector contains all the data on the applied LTs, MFs and their set parameters. The **R** vector includes all the generated rules of the rule base. The $\mathbf{LT}(W_b, Q_c, Q_p)$ vector contains all the LTs for the input variables of the system W_b, Q_c and Q_p. The $\mathbf{LT}(\eta)$ vector is a vector of all LTs for the output variable of the system η. The $\mathbf{LT}_{ins}$ vector includes the selected LTs of the input variables used to fuzzify their current values. The $\boldsymbol{\mu}_{LTin}$ vector is a vector of the degrees of membership of the selected LTs of the input variables used to fuzzify their current values. The vector $\mathbf{A}_s$ is the vector of antecedents of the rules formed by the selected LTs, and the vector $\mathbf{C}_s$ is the vector of consequents of the rules corresponding to the formed antecedents As. The vector $\boldsymbol{\alpha}_A$ includes the degrees of membership of the antecedents of the involved rules, which are found based on the "min" operation. The vector $\mathbf{LT}_{st}(\eta)$ is the vector of the degrees of membership of the consequents of the involved rules (truncated membership functions), which are also found using the "min" operation. The output signal of the ACC block $\mu_\Sigma(\eta)$ is the resulting fuzzy subset, which is obtained by combining the truncated membership functions of $\mathbf{LT}_{st}(\eta)$ based on the "max" operation. In turn, the output signal η of the presented DSS is formed by the defuzzification block by extracting a clear (numerical) value from the resulting fuzzy subset $\mu_\Sigma(\eta)$ using the center of gravity method.

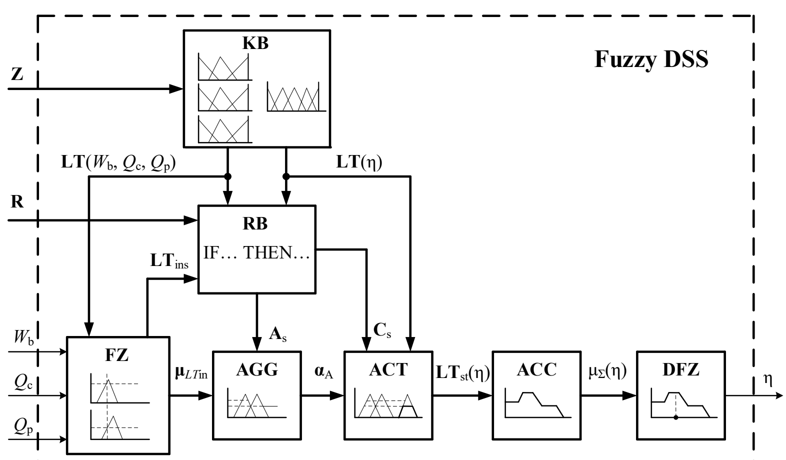

Fig. 1. Structural diagram of a fuzzy DSS for assessing the effectiveness of artillery fire

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At the initial stage of designing the proposed fuzzy DSS, data on linguistic terms for all input and single output variables are entered into the knowledge base. In particular, each input variable, the working range of which is set from 0 to 1, is divided into several linguistic terms to ensure a certain granularity of the input information. In this case, it is advisable to choose from three to five terms for each of the three input variables. Similarly, the working range [0, 1] of the output variable η is divided into several LTs, the number of which can be set from 5 to 9 to ensure flexibility and variability of decision-making strategies. After that, the types of membership functions are selected for each LT. The given MF can be chosen as the same for all terms of a certain variable (input or output), or different (for each individual LT) for the most accurate reproduction of the desired relationships between the input and output variables [40]. The most common in the construction of control and decision-making systems for various purposes are Gaussian, triangular or trapezoidal MFs due to their interpretability and relative simplicity of modeling [41]. For example, the mathematical description of these functions for the first input variable W_{b} is presented in the expressions:

$$\mu\left(W_{\text{b}}\right)=e^{-\frac{\left(W_{\text{b}}-b\right)^2}{2a^2}}; \tag{5}$$

$$\mu(W_{\text{b}})=\begin{cases}0, \text{ at } W_{\text{b}}\le a;\\ \dfrac{W_{\text{b}}-a}{b-a}, \text{ at } a<W_{\text{b}}\le b;\\ \dfrac{c-W_{\text{b}}}{c-b}, \text{ at } b<W_{\text{b}}<c;\\ 0, \text{ at } W_{\text{b}}\ge c;\end{cases} \tag{6}$$

$$\mu(W_{\text{b}})=\begin{cases}0, \text{ at } W_{\text{b}}\le a;\\ \dfrac{W_{\text{b}}-a}{b-a}, \text{ at } a<W_{\text{b}}\le b;\\ 1, \text{ at } b<W_{\text{b}}\le c;\\ \dfrac{d-W_{\text{b}}}{d-c}, \text{ at } c<W_{\text{b}}<d;\\ 0, \text{ at } W_{\text{b}}\ge d,\end{cases} \tag{7}$$

where a, b, c, d – the parameters of the MF data to be adjusted.

In turn, for the proper specification and further calculation of the above MFs, certain restrictions must be observed. In the case of a triangular function: $a \le b \le c$. For a trapezoidal MF: $a \le b \le c \le d$. In addition, the parameters of these functions must be set in such a way that all LTs of each variable evenly overlap its operating range.

The next stage of design involves compiling a rule base, which is the core of a fuzzy decision support system. The size of this rule base is determined by the total number of all unique combinations of LTs of the input variables that form the antecedents of fuzzy rules. These combinations are usually generated by sequentially searching through all possible terms of each input variable. The consequences for each of the rules are determined by experts from the full set of LTs that are applied to the output variable. Each rule base can be formed in a generalized form as follows

$$\begin{aligned}&\text{IF "}W_{\text{b}}=LT_{1i}\text{" AND "}Q_{\text{c}}=LT_{2j}\text{" AND "}Q_{\text{p}}=LT_{3k}\text{"}\\ &\text{THEN "}\eta=LT_{4g}\text{",}\end{aligned} \tag{8}$$

where LT_{1i}, LT_{2j}, LT_{3k}, LT_{4g} – the i-th, j-th, k-th and g-th linguistic terms of the corresponding system variables W_{b}, Q_{c}, Q_{p} and η.

After constructing the complete matrix of antecedent relationships with the corresponding consequences, the formation of the rule base is considered complete.

At the final stage of the development of a fuzzy DSS, the parameters of linguistic terms are refined and the rule base is adjusted to ensure high efficiency of operation. If incorrect values of the output variable are detected during the system testing process for certain combinations of input variables, then corrective tuning is necessary [42]. This procedure may include adjusting the values of the parameters of the membership functions of certain LTs, changing their form or rearranging the consequences of certain rules. Such iterative refinement must be carried out until the system's output responses meet the expectations of experts and accurately reflect the planned decision-making logic. Carrying out this stage allows to fine-tune the fuzzy DSS to achieve high interpretability and the necessary accuracy of reproducing the desired dependencies of the input and output variables.

Next, let's consider some aspects of the application of the presented system. When using the presented fuzzy DSS, the structure of which is presented in Fig. 1, the operator must first enter the current values of barrel wear, as well as the quality of charges and shells. These parameters are determined by the operator or other qualified experts who are at the firing positions. After entering these initial data, the system operates in an autonomous mode during the firing of the entire batch of ammunition, without requiring further adjustment of the values of the input variables. However, this approach has significant limitations, since it does not take into account the current wear of the gun barrel, which is constantly increasing during firing with the current batch of ammunition, and also neglects feedback on the accumulated real firing results. To take into account these dynamic factors and ensure continuous correction of the predicted value of the firing efficiency in real time after each shot, it is advisable to use the hybrid architecture of the fuzzy DSS proposed by the authors. This improved system is discussed in detail and experimentally verified in the next subsection.

3. Results and Discussion

3.1. Architecture of a hybrid fuzzy DSS for a comprehensive assessment of the effectiveness of artillery fire

To take into account the gradual wear of the gun barrel, which occurs as a result of each subsequent shot when using the current batch of shells and charges, it is advisable to modify the system in the following way. Namely, it is proposed to feed the value of barrel wear set by the operator not directly to the input of the fuzzy system, but through a specialized correction module. In this case, the wear value set by the operator will be considered as a preliminary estimate W_{b0}, while the corrected value obtained through the correction module will be the actual wear value W_{b}. The latter should be calculated using dependencies (2) or (3), which describe the relationship between the wear of the barrel W_{b} and the number of shots fired N_{sh}. At the same time, in these formulas, instead of simply substituting the current number of shots N_{sh}, the sum $(N_{\text{sh0}} + N_{\text{sh}})$ should be used, in which N_{sh0} denotes the previous number of shots already fired that caused this wear. In turn, the previous number of shots N_{sh0} can be calculated quite easily using the inverse dependencies (9) or (10), into which the initial value of wear W_{b0} given by the operator is substituted:

$$N_{\text{sh0}}=\begin{cases}\dfrac{W_{\text{b0}}-b_{\text{w1}}}{k_{\text{w1}}}, \text{ at } 0<W_{\text{b0}}\le W_{\text{b1}};\\ \dfrac{W_{\text{b0}}-b_{\text{w2}}}{k_{\text{w2}}}, \text{ at } W_{\text{b1}}<W_{\text{b0}}\le W_{\text{b2}};\\ \dfrac{W_{\text{b0}}-b_{\text{w3}}}{k_{\text{w3}}}, \text{ at } W_{\text{b2}}<W_{\text{b0}}<1;\\ N_{\text{shmax}}, \text{ at } W_{\text{b0}}=1,\end{cases} \tag{9}$$

where W_{b1} and W_{b2} – certain specified values of wear, at which the slope of the characteristic changes;

$$N_{\text{sh0}}=\beta-\frac{1}{\alpha}\ln\left(\frac{1}{W_{\text{b0}}}-1\right). \tag{10}$$

If the dependence (2) with several linear sections is chosen, then the corresponding inverse function (9) should be used. In turn, when using the sigmoid function (3), the corresponding inverse expression will be formula (10). In addition, to take into account the influence of the quality of charges and shells in the current batch on barrel wear, it is advisable to adjust the linear coefficients in the dependences (2) and (9) as follows:

$$k_{w1}=\frac{k_{w10}}{Q_c Q_p};$$
$$k_{w2}=\frac{k_{w20}}{Q_c Q_p};$$
$$k_{w3}=\frac{k_{w30}}{Q_c Q_p}, \qquad (11)$$

where k_{w10}, k_{w20} and k_{w30} – the values of the coefficients that determine the corresponding slopes of the characteristic at the nominal quality indicators of shells and charges.

Also, for dependencies (3) and (10), the coefficients β and α should be determined based on the following expressions proposed by the authors:

$$\beta = N_{sh0.5} Q_c Q_p; \qquad (12)$$

$$\alpha=\frac{k_r}{\beta}, \qquad (13)$$

where $N_{sh0.5}$ – the number of shots that leads to barrel wear $W_b = 0.5$ (for a specific type of artillery system) at nominal quality indicators of shells and charges; k_r – the regulating coefficient.

Taking into account the assessment of the real efficiency of artillery fire and adjusting the forecast value after each subsequent shot from the current batch of ammunition in this system is advisable to do as follows. Namely, the output signal of the fuzzy system is proposed to be considered as a preliminary model estimate η_m and combined with the real efficiency estimate η_r, which is determined after each shot based on expression (4). The resulting adjusted value of the operational efficiency of firing η is advisable to calculate by aggregating the two above-mentioned components (η_m and η_r) using expression (14), which allows to constantly refine the obtained estimate in real time

$$\eta=\eta_r K_A+\eta_m\left(1-K_A\right), \qquad (14)$$

where K_A – the aggregation coefficient, which is calculated as the ratio of the number of all shots N_{sh}, already fired at the current time from a given batch of ammunition, to the total number of planned shots $N_{sh\Sigma}$ from this batch for the current firing task

$$K_A=\frac{N_{sh}}{N_{sh\Sigma}}. \qquad (15)$$

In turn, the total number of planned shots $N_{sh\Sigma}$ is predetermined either by the specifics of the firing task, or by the total number of shells and charges in the available batch.

Thus, the architecture of the proposed hybrid fuzzy DSS, which takes into account all the above aspects, is shown in Fig. 2.

Next, let's consider the main elements of this architecture. The WVCU (wear value correction unit) block corrects the wear value by implementing either dependencies (2), (9), (11), or expressions (3), (10), (12), (13). The UFMC (unit of fire monitoring and control) block records successful shots N_{shs} and the total number of shots fired N_{sh} based on the vector **X**. In this case, the vector **X** is a vector of all the main parameters that characterize the functioning of the artillery installation and the state of the environment. The RECU (real efficiency calculation unit) block calculates the current real value of the efficiency η_r using expression (4) based on the number of successful shots N_{shs} and the total number of shots N_{sh}. The aggregation coefficient calculation unit ACCU calculates the current value of the K_A coefficient based on expression (15), using the number of shots already fired N_{sh} and the total number of planned shots $N_{sh\Sigma}$. In turn, the fuzzy subsystem FSS has the structure shown in Fig. 1.

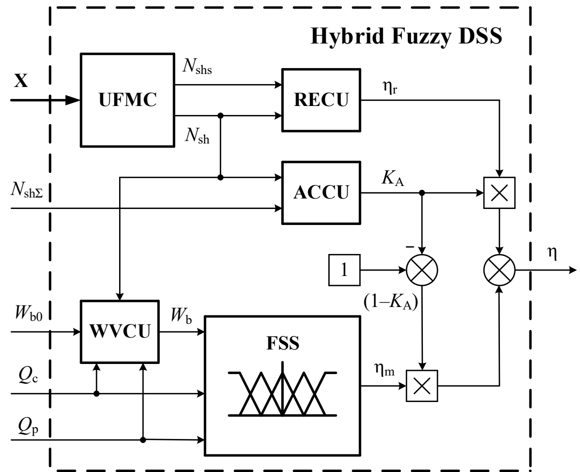


Fig. 2. Structural configuration of hybrid fuzzy DSS for assessing the effectiveness of artillery fire

3.2. Development of a fuzzy subsystem for determining a preliminary assessment of the effectiveness of artillery fire

Next, let's consider in more detail the procedure for developing the fuzzy subsystem FSS, which is the main component of the proposed hybrid DSS. At the initial stage, the knowledge base of this subsystem was filled with the following linguistic terms with specified parameters (Table 1).

Table 1

Data of linguistic terms of the fuzzy subsystem

No.	Linguistic term	Membership function	Parameter values
The first input variable W_b (barrel wear)			
1	NB – new barrel	Gaussian	a = 0.1062; b = 0
2	MW – minor wear	Gaussian	a = 0.1062; b = 0.25
3	AW – average wear	Gaussian	a = 0.1062; b = 0.5
4	SW – significant wear	Gaussian	a = 0.1062; b = 0.75
5	CWO – completely worn out	Gaussian	a = 0.1062; b = 1
The second input variable Q_c (quality of charges)			
1	LQ – low quality	trapezoidal	a = 0; b = 0; c = 0.4; d = 0.5
2	AQ – average quality	triangular	a = 0.4; b = 0.7; c = 0.9
3	HQ – high quality	triangular	a = 0.8; b = 1; c = 1
Third input variable Q_p (projectile quality)			
1	LQ – low quality	trapezoidal	a = 0; b = 0; c = 0.4; d = 0.5
2	AQ – average quality	triangular	a = 0.4; b = 0.7; c = 0.9
3	HQ – high quality	triangular	a = 0.8; b = 1; c = 1
Output variable η_m (model fire efficiency)			
1	VLE – very low efficiency	triangular	a = 0; b = 0; c = 0.167
2	LE – low efficiency	triangular	a = 0; b = 0.167; c = 0.333
3	BAE – below average efficiency	triangular	a = 0.167; b = 0.333; c = 0.5
4	AE – average efficiency	triangular	a = 0.333; b = 0.5; c = 0.667
5	AAE – above average efficiency	triangular	a = 0.5; b = 0.667; c = 0.833
6	HE – high efficiency	triangular	a = 0.667; b = 0.833; c = 1
7	VHE – very high efficiency	triangular	a = 0.833; b = 1; c = 1

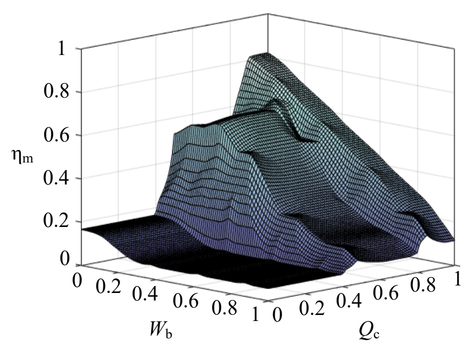
After that, a rule base was created for the fuzzy subsystem (Table 2), which consists of 45 rules specified by expressions of the form (8). In turn, the inner part of Table 2 contains the corresponding consequents of the rules.

Table 2

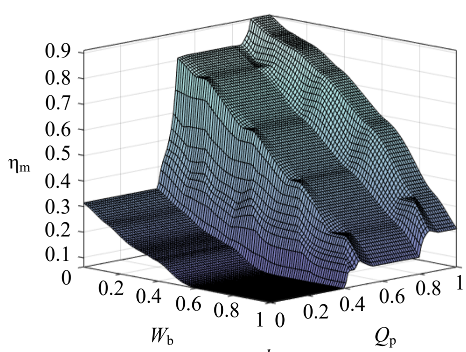
Matrix of the rule base of the fuzzy subsystem

LT for Q_p	LT for Q_c	LT for W_b				
		NB	MW	AW	SW	CWO
LQ	LQ	VLE	VLE	VLE	VLE	VLE
	AQ	LE	VLE	VLE	VLE	VLE
	HQ	BAE	LE	VLE	VLE	VLE
AQ	LQ	LE	VLE	VLE	VLE	VLE
	AQ	AE	AAE	BAE	LE	VLE
	HQ	HE	AAE	AE	BAE	VLE
HQ	LQ	BAE	LE	VLE	VLE	VLE
	AQ	HE	AAE	AE	BAE	VLE
	HQ	VHE	HE	AAE	AE	LE

For greater clarity and ease of understanding of the principles of functioning of the developed fuzzy subsystem, Fig. 3 shows its three-dimensional dependences of the output on the inputs.



a



b

Fig. 3. Three-dimensional dependences of the output on the inputs of the developed fuzzy subsystem: *a* – $\eta_m = f(W_b, Q_c)$ at $Q_p = 0.75$; *b* – $\eta_m = f(W_b, Q_p)$ at $Q_c = 0.9$

In particular, Fig. 3, shows the dependence of the model efficiency of artillery fire on barrel wear and charge quality for a fixed value of projectile quality of 0.75. In turn, Fig. 3, *b* shows the change in fire efficiency as a function of barrel wear and projectile quality for a fixed value of charge quality at 0.9. Since the obtained surface characteristics quite accurately reproduce the relationships embedded in the rule base, no additional tuning of the developed fuzzy subsystem was carried out.

3.3. Study of the effectiveness of the developed hybrid DSS

A series of computational experiments was conducted to study the effectiveness of the proposed hybrid fuzzy decision support system. In particular, three simulation experiments were conducted to simulate firing from an artillery gun with an initial barrel wear rate $W_{b0} = 0.1$ using a batch of 100 shells (charge quality $Q_c = 0.9$, projectile quality $Q_p = 0.8$). The full barrel life to final wear was chosen to be 1700 shots, and accordingly the wear level $W_b = 0.5$ was considered to be achieved after 850 shots ($N_{sh0.5} = 850$). To simulate the real firing process with this batch of ammunition with 100 shells and 100 charges with successful and unsuccessful hits, a random process was taken. In this case, the probability of successful shots was set to a value that does not exceed the instantaneous model estimate of the firing efficiency η_m obtained using a fuzzy subsystem. Since the random processes of artillery firing were simulated, different results were obtained in each of these three experiments. In addition, in these experiments, the change in the current value of barrel wear, which was constantly accumulated during firing, was simulated using dependencies (3), (10), (12) and (13).

Similarly, three other experiments were conducted to study the functioning of the hybrid DSS in the second artillery firing scenario: initial barrel wear $W_{b0} = 0.25$, batch size 100, charge quality $Q_c = 0.6$, projectile quality $Q_p = 0.7$. For this gun, the value of the full barrel resource to final wear was chosen to be 2400 shots (therefore, the wear value $W_b = 0.5$ corresponded to the number of shots $N_{sh0.5} = 1200$). In these experiments, a similar stochastic modeling procedure and the same relationships of the dependence of the current wear on the number of shots fired were used as for the first three experiments. The results of all six computational experiments for two different shooting scenarios are presented in Fig. 4–9 and are discussed below.

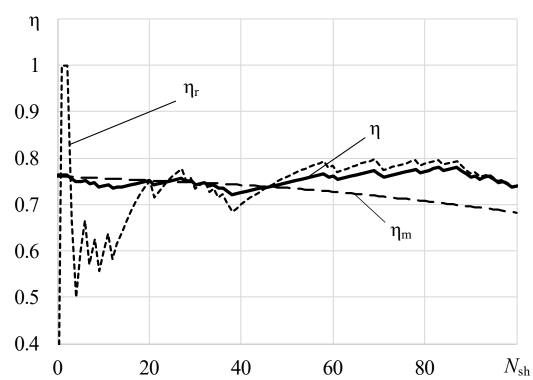


Fig. 4. Graphs of changes in the values of firing efficiency η depending on the number of shots fired N_{sh} at $W_{b0} = 0.1$, $Q_c = 0.9$, $Q_p = 0.8$, $N_{sh0.5} = 850$ (Experiment 1)

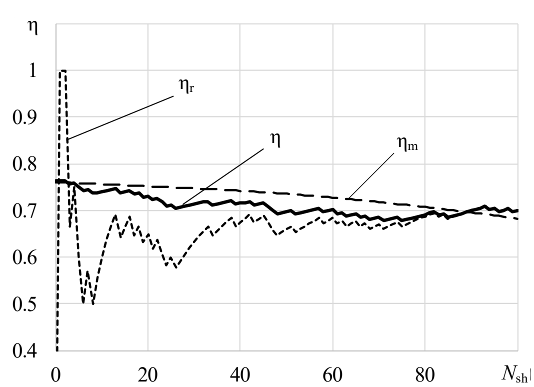


Fig. 5. Graphs of changes in the values of firing efficiency η depending on the number of shots fired N_{sh} at $W_{b0} = 0.1$, $Q_c = 0.9$, $Q_p = 0.8$, $N_{sh0.5} = 850$ (Experiment 2)

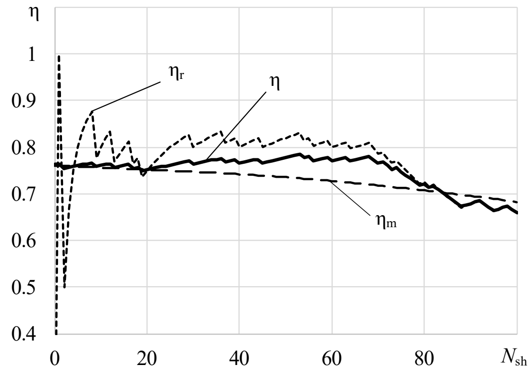


Fig. 6. Graphs of changes in the values of firing efficiency η depending on the number of shots fired N_{sh} at $W_{b0} = 0.1$, $Q_c = 0.9$, $Q_p = 0.8$, $N_{sh0.5} = 850$ (Experiment 3)

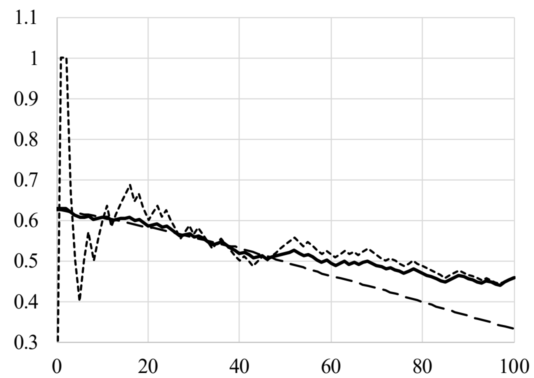


Fig. 7. Graphs of changes in the values of firing efficiency η depending on the number of shots fired N_{sh} at $W_{b0} = 0.25$, $Q_c = 0.6$, $Q_p = 0.7$, $N_{sh0.5} = 1200$ (Experiment 4)

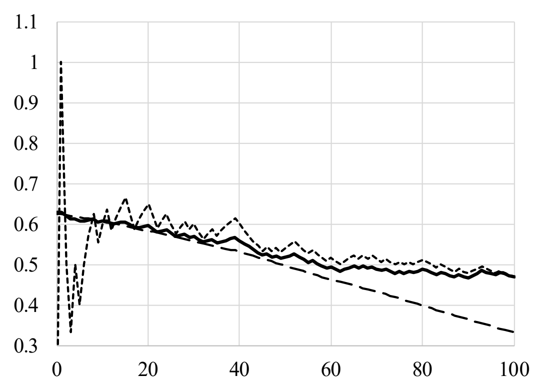


Fig. 8. Graphs of changes in the values of firing efficiency η depending on the number of shots fired N_{sh} at $W_{b0} = 0.25$, $Q_c = 0.6$, $Q_p = 0.7$, $N_{sh0.5} = 1200$ (Experiment 5)

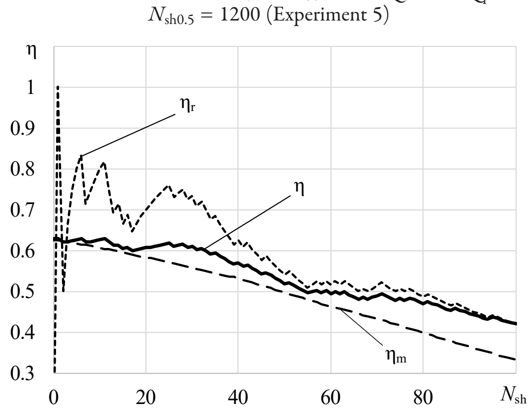


Fig. 9. Graphs of changes in the values of firing efficiency η depending on the number of shots fired N_{sh} at $W_{b0} = 0.25$, $Q_c = 0.6$, $Q_p = 0.7$, $N_{sh0.5} = 1200$ (Experiment 6)

In turn, each of the above graphs of the simulation results (Fig. 4–9) shows the dynamics of changes in the three main efficiency indicators as functions of the number of shots fired: η_m, η_r and η. In particular, the model efficiency value η_m was generated by the fuzzy subsystem, the real efficiency value η_r was calculated based on the results of the simulation of firing processes ($N_{sh} = 0$–100). In turn, the resulting adjusted efficiency value η was calculated by the hybrid DSS. The obtained dependencies of the model, experimental and resulting efficiency values show that the hybrid system performs real-time estimation refinement after each shot based on the accumulated firing results. The results of the simulation experiments demonstrate that the developed hybrid fuzzy DSS provides a highly accurate assessment of the overall firing efficiency for a specific artillery installation firing using a certain batch of charges and shells under conditions of uncertain disturbances. In addition to the initial value of barrel wear, which was determined by the operator before the start of firing, the proposed system also takes into account the current wear, which increases after each shot with shells and charges from the current batch. This allows to significantly increase the accuracy of calculating the efficiency assessment. Moreover, the hybrid DSS constantly takes into account the real results of already fired shots to ensure adaptive refinement of the efficiency throughout the execution of the firing task. Analysis of the obtained results (Fig. 4–9) shows that at the initial stages of firing, when a relatively small number of shots have been fired, and the calculated value of the real efficiency based on the results of these shots fluctuates significantly, the output of the hybrid system is mainly determined based on the calculated estimate of the fuzzy model. In turn, with the accumulation of certain firing results using ammunition from the current batch, the contribution of experimental data to the formation of the system output signal gradually increases. Thus, the system acquires adaptive properties, which confirms the high efficiency and validity of the proposed approach to aggregation of estimates based on expression (14). In general, the calculated efficiency values during the entire firing process changed by no more than 12% in the first three experiments and no more than 21% in the next three. At the same time, in the case of the second group of experiments (experiments 4–6), this deviation is primarily explained by the accelerated wear of the barrel under the specified operating conditions due to the lower quality of the shells and charges that were used. Thus, the obtained results of the simulation experiments fully confirm the correct functioning and high efficiency of the developed hybrid fuzzy DSS.

The limitations of the practical application of the proposed hybrid fuzzy DSS for assessing the effectiveness of artillery fire include the following. In the case of incorrect determination by the operator of the current values of barrel wear or the quality of shells and charges, the model estimate of the effectiveness calculated by the fuzzy subsystem may differ significantly from the real value. To reduce this risk, additional corrective feedback loops can be introduced into the proposed system, for example, based on sensors that measure the actual initial exit velocity of the projectile. Sensors placed along the projectile flight path can also be used to record its velocity at certain points, as described in [26, 35]. Integration of such feedback channels will allow the system to detect discrepancies in the initially specified input parameters and signal the presence of incorrectly defined variables.

An additional problem may arise when several experts are present at the firing positions, and their assessments of the current values of the input data differ. To eliminate this problem at the stage of formalization of the input data, it is advisable to use group decision-making methods. Improvement of the proposed DSS based on the application of these methods is planned in further research. Further research can also be aimed at solving the problems of structural-parametric optimization of the developed hybrid fuzzy DSS using modern intelligent algorithms [41]. In addition, refinement of the mathematical description of the barrel wear characteristics can be implemented using experimental studies and highly effective identification methods [43].

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4. Conclusions

1. A functional architecture of a hybrid fuzzy DSS has been developed, which allows integrating both model and experimental data in the process of determining efficiency estimates. Its fuzzy subsystem determines the model value of firing efficiency based on expert knowledge formalized using fuzzy logic. This value is constantly adjusted taking into account the current barrel wear that accumulates during continued firing. At the same time, the system takes into account statistical information obtained during firing with the current batch of shells and charges, calculating the real firing efficiency. The resulting fire efficiency value is calculated by aggregating model and real efficiency estimates, which ensures adequate functioning of the system at all stages of firing with ammunition from the current batch.

2. A Mamdani-type fuzzy subsystem has been synthesized, which is the main component of the proposed hybrid DSS. The given subsystem has 45 rules in the rule base and allows to calculate the model value of artillery fire efficiency based on the current values of barrel wear, charge and shell quality entered by the operator.

3. To study the efficiency of the developed hybrid DSS, six computational experiments were conducted. The first three experiments were for a setup with initial barrel wear of 0.1 and high-quality charges and shells ($Q_c = 0.9$, $Q_p = 0.8$). The next three experiments were for another setup with initial wear of 0.25 and lower-quality ammunition ($Q_c = 0.6$, $Q_p = 0.7$). The obtained results demonstrated high efficiency and robustness of the proposed hybrid fuzzy DSS in all six experiments, which confirms the feasibility of its application in controlling artillery systems in variable and uncertain conditions. The use of this system allows artillery system operators to make informed decisions on the advisability of continuing or ceasing fire during combat missions in current operational conditions to minimize risks.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The research was performed without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in creating the submitted paper.

Authors' contributions

***Maksym Maksymov**:* Conceptualization, Validation, Writing – review and editing, Supervision; ***Oleksiy Kozlov**:* Conceptualization, Methodology, Formal analysis, Writing – review and editing; ***Oleksiy Maksymov**:* Methodology, Software, Formal analysis, Writing – original draft; ***Ruslan Riaboshapka**:* Methodology, Software, Writing – original draft.

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